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Application of Neural Network in Shop Floor Quality Control in a Make to Order Business

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Abstract

A make to order business has to produce the products that are customized to the customer's current need. The customization can be realized by assembling different standard parts with various 'configurations'. The oil field service industry is a typical example where most products produced are cylindrical assemblies made up of standard parts customized in their size, material specifications, coating specifications, and threading suited for the particular load rating and environment. As business cycles go up and down, hiring and firing of personnel is the routine of the day. Thus, it is very hard to keep experienced inspectors due to high turnover of the staff on shop floor and thus intensive endeavor to train the inspectors for the same recurrent problems of the same standard parts is required. This paper proposes a neural network model to help the industrial practitioners address such a concern. The neural network is trained with ample 'judgment calls' from the manufacturing experts so that it can properly generate the decision to 'scrap', 'rework' or 'use as is' for the inspected parts. The real quality data from an oil field service industry is used to validate the effectiveness of the proposed tool.

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Keywords: Neural Network; Quality Control; Make to Order Business

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1. Introduction

Globalization has made operation in different economies an essential strategy for many industrial practitioners. This high level of competition amongst manufacturers has led to rapid development in the different manufacturing paradigms such as computer integrated manufacturing[1], flexible manufacturing[2], agile manufacturing[3], and intelligent manufacturing[4]. Such development has in turn generated a need for intelligent sensing and decision making systems capable of automatically performing many tasks traditionally executed by human beings[3].

Specifically, in such a business environment, a make-to-order manufacturing industry has to operate under additional constraints in comparison to standard mass manufacturing enterprises. The traditional manufacturing buzzwords like lean, six sigma, and kaizen may not be directly used on the actual shop floor due to the presence of a high degree of customization offered in their product portfolio. Most of the lessons learned and experience obtained may be limited to a small part of experienced manufacturing personnel and cannot be translated into effective process standards and widespread to the entire team on the shop floor due to high turnover of plant staff, which is used as a major labor strategy to deal with a highly cyclic and volatile business environment (e.g., oil industry).

In addition, manufacturing companies tend to benefit from the cost advantages available in developing economies. They try to achieve the same production quality considering the fact that different levels of skill and education do exist amongst manufacturing personnel in different countries. Thus, a burgeoning demand for "smart systems" consisting of advanced machine learning tools that are capable of retaining experience and automating low end repetitive work has been generated. The advantage of such "smart systems" is that they can utilize the reliability and speed of computers, while offering the flexibility and cognitive abilities of human beings[5], so that some repetitive and labour-intensive tasks (e.g., quality inspection) originally executed by human beings on shop floor can be implemented by such "smart systems". The training cost for the new employed employees can be reduced and the reliability of the results of such tasks can be improved.

In this paper, we explore the feasibility of the utilization of neural network (NN) approach, a typical machine learning tool, for the application of quality inspection in oil industry. The rapid growth in automated manufacturing has made full-fledged human like intelligent machines possible[5]. This has provided a solid basis and environment where advanced "smart systems" can be implemented. The replacement of manual inspection procedures through the introduction of automated techniques offers a number of significant commercial and social advantages, including elimination of human error and/or subjective judgment, improved operational efficiency, creation of timely statistical product data, improved safety, better working conditions, and reduced labour costs[6].

NN is an adaptive learning mechanism which is able to learn and expand its experience continuously. It is an effective tool to allow the machine to do the repetitive tasks. In addition, the speed and accuracy provided by today's computing power can enable manufacturing units to achieve needed cost edge in today's market. NN is unique in comparison to traditional approaches regarding its ability to learn and make associations between new patterns and cluster data. It can recall the information once the network is presented with similar input[5]. The back propagation algorithm in NN is able to provide better results with sparser data compared with statistical approaches[7]. Several advantages such as processing speed, adapting ability, and robustness of the NN application in manufacturing applications have been enumerated in the literature[8]. The NN applications in manufacturing areas such as design, scheduling, process planning, and control have also been discussed[8], e.g., manufacturing stock price prediction[9], crude oil price forecasting[10], etc.

Regarding the application in quality control, several research has also been reported[11, 12, 6 and 13]. For example, NN application in textile seam (one type of defect) identification has been carried out by means of a self-organising map algorithm[11]. It employed image acquisition, feature extraction, and classification for locating the defect (seam). Another example is that the detection of causes of casting defects has been carried out through NN[12] using simple multilayer feed forward networks.

In this study, NN is applied to shop floor quality inspection in a make-to-order manufacturing enterprise in the oil field service industry using real data from our industrial collaborator. The decisions regarding 'Scrap', 'Rework', and 'Use as is' will be generated using NN approach. The results in terms of accuracy percentage using different NN algorithms will be obtained and compared to the manual inspection. The best algorithm will be recommended. The rest of the paper is organized as follows. Section 2 discusses the research methodology. It lists the data source, the preprocessing for the raw data, the NN architectures used, and the performance evaluation criteria. Section 3 demonstrates the results obtained. Section 4 concludes the paper and discusses the future work.

2. Methodology

A Matlab-based NN is designed to do two-phase binary classification for the data as shown in Fig. 1. In the first phase, the NN will evaluate if the part under consideration can be used as is. A back propagation with momentum NN and a radial basis functions are used and compared in NN. The second phase of the classification is focused on the remaining data that the results of the first phase is "cannot be used as is". It is again a binary classification to identify if the part can be reworked or it has to be scrapped. The use of such a two-step binary classification rather than a one-step ternary classification is mainly due to our industrial collaborator's concern that the misclassification cost will be high when 'use as is' and 'scrap' are combined in a single classification. On one hand, if an actual 'use as is' part is classified as 'scrap', it will lead to loss of value of the part. On the other hand, if an actual 'scrap' part is classified as 'use as is', it will definitely lead to both direct loss and indirect losses including loss of business, safety issues, etc.

Since phase II is much more intricate, a radial basis network which will make the data points linearly separable in a higher dimension is employed as well as the algorithm of back propagation with momentum. For comparison, we also employ a support vector machine which will classify two different sets using the boundary set points and hence ensure the accuracy of classification. A performance comparison will be made among the back propagation with momentum, radial basis functions, and support vector machines[15].

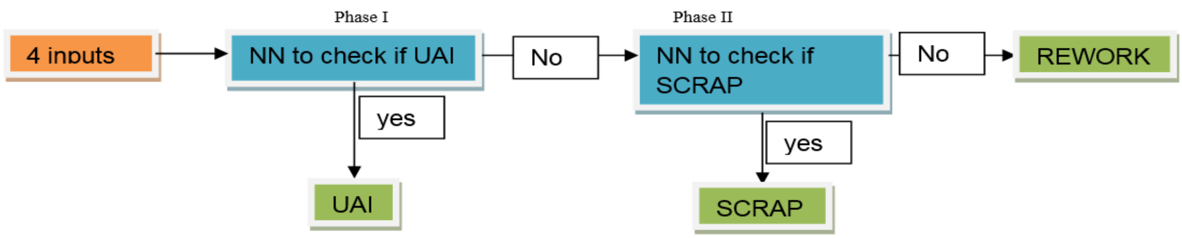

Fig.1. Neural Network Strategy

2.1. Data preprocessing

The raw data from an oil field service industry collaborator consisting of approximately 4200 quality notifications (defect notifications) from four different manufacturing plants of a company over a period of one year is provided. As the plants make a variety of tools, a candidate tool has to be identified for the NN application. This candidate must have ample data in the total dataset and also should give considerable variety over the problem space. After a lot of sorting, the 'Mandrel' was shortlisted as the appropriate target for the NN application.

A mandrel can be the chassis of an oil tool. It is the part on which all other parts are assembled. A mandrel basically consists of upper-threads, bevels to shoulder onto other tools, outside diameter profile, a seal bore, and lower-threads as the main parts as shown in Fig. 2. Furthermore, they may contain grooves, pin holes, thread reliefs, hone reliefs, etc.

There were a total of 627 quality notification cases for mandrels in the original dataset that can be used as the inputs to the NN. Specifically, the answers to the following four questions are defined as four inputs to the NN model:

- X1 - Is the defect due to in-house manufacturing or due to some process done by a vendor? (-1for vendor and +1 for in-house)
- X2 - Where does defect occur? (28 different locations equally spaced marked by values between -1 and 1)
- X3 - What kind of defect? (Six different types of defects equally spaced marked by values between -1 and 1)
- X4 - What is the severity of the defect? (-1 for severe and +1 for not severe)

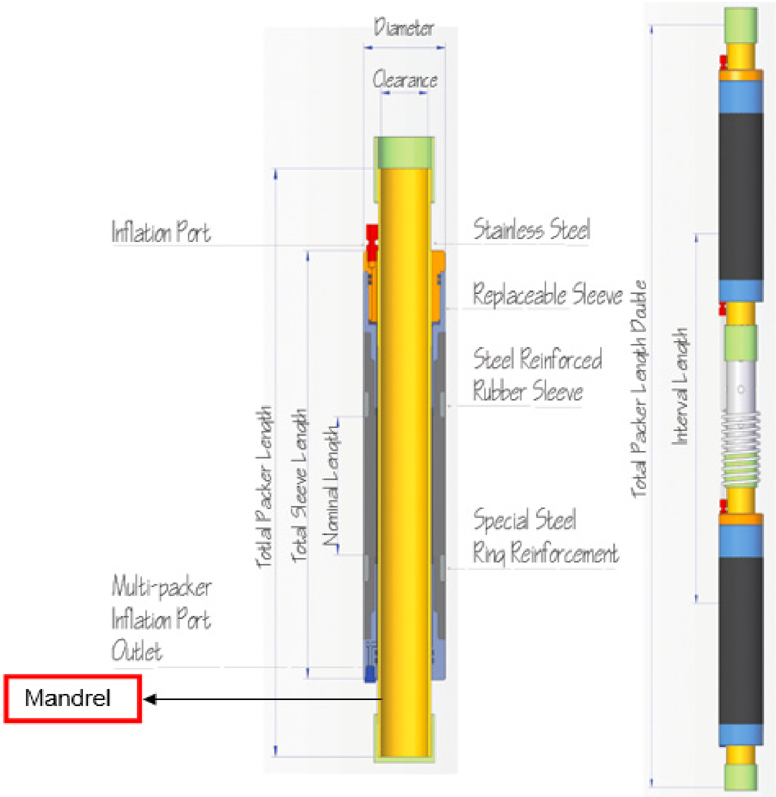

Fig. 2. Mandrel

2.2. Neural network design

The architecture of the selected NN as shown in Fig.1 includes two NNs for both binary classifications for the two-phase decision-making. The first NN classifies whether the part can be used as is. Two architectures are tested: back propagation with momentum NN, and radial basis function. All the four inputs X1, X2, X3 and X4 are given as inputs to the system and the classification result Y1 is recorded. The second NN works on the remaining data which does not qualify to be "used as is". It classifies whether the part has to be scrapped or reworked. Three different architectures are examined, i.e., back propagation with momentum algorithm, radial basis functions, and support vector machines. The NN structure of back propagation with momentum algorithm and radial basis functions is shown in Fig. 3.

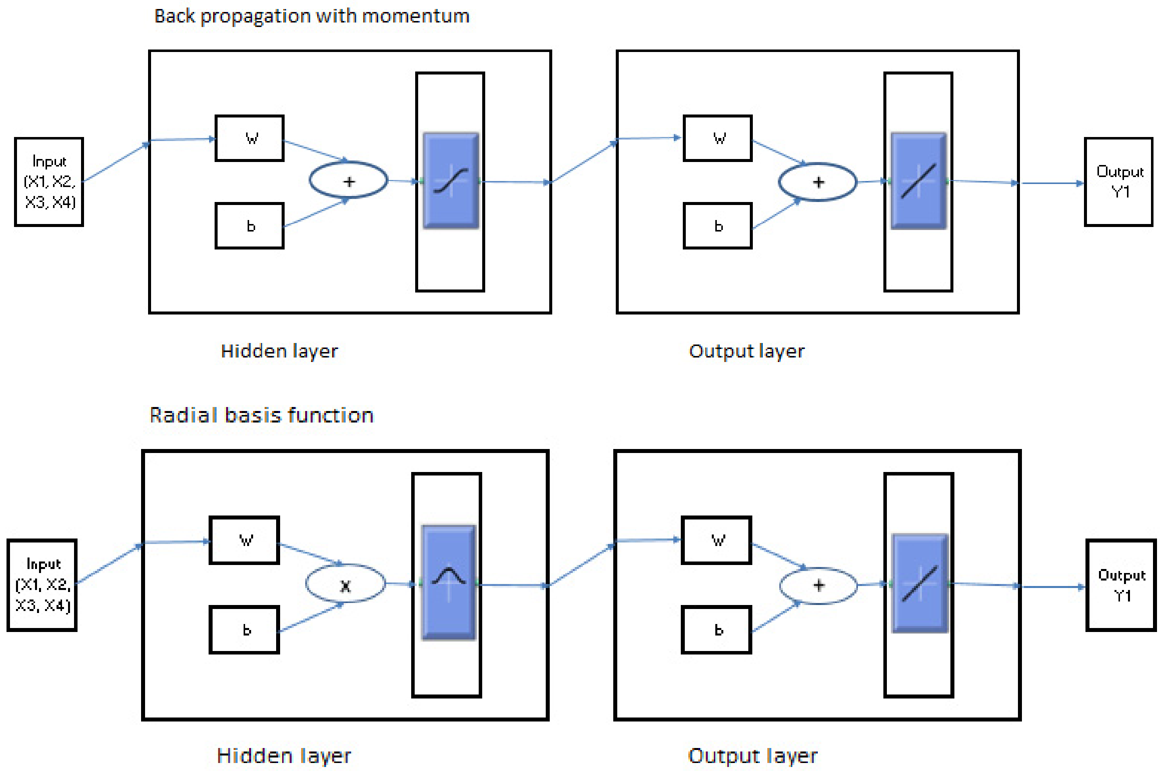

Fig. 3. NN Architectures employed

2.3. Performance evaluation:

The data is divided into training and testing with a 70:30 ratio. The approaches for the two phases are discussed below:

Phase I:

The training and testing datasets consist of 440 and 188 points, respectively. Two different NNs are employed. The first one is a back propagation algorithm with momentum. Different combinations of learning parameter, momentum parameter, and the number of neurons are tried to find optimal performance. The second one is the radial basis function algorithm. Different spread constants and number of neurons are tried to find out the optimal network configuration.

Phase II:

The training and testing datasets consist of 260 and 110 points, respectively. The decision making for this phase is much trickier than phase I. For example, if a critical dimension has an error of 0.001 inch, this could be the boundary for the decision of scrap or rework. Thus, three different NNs are employed. The first one is a back propagation with momentum. Different combinations of learning parameter, momentum parameter, and the number of neurons are tried to identify optimal performance. The second is the radial basis function algorithm. Different spread constants and number of neurons are tried to seek the optimal network configuration. The third one is the support vector machine algorithm. Different misclassification costs (Box Constraint in Matlab), or C values, are examined. The data is post processed to get the classification results very close to -1 or 1.

3. Results

Phase I:

Table 1 shows the results of the back propagation with momentum algorithm. The network performs well with a small learning rate of 0.01 or 0.1. It allows that the weights can be gradually adjusted and so the entire dataset can be gone through. When the learning rate is at 0.5 combined with a momentum parameter of 0.1, the network does not perform well. Best performance is obtained with 10 neurons, a learning rate of 0.1, and momentum parameter of 0.25.

Table 2 shows the results of the radial basis function network. The overall performance is slightly better when the number of neurons is increased from 10 to 20. With 10 neurons, performance is best with a spread constant of 0.25. With 20 neurons, performance is best with a spread constant of 0.5. Table 3 shows the confusion matrix of the best case.

Table 1. Summary of back propagation algorithm for Phase I

# Neurons	Training time (seconds)	Epochs	Learning rate	momentum parameter	% correct
10	1	1000	0.01	0.5	97.87
10	1	179	0.5	0.1	40.96
10	1	1000	0.1	0.25	100
20	1	1000	0.01	0.5	89.89
20	1	129	0.5	0.1	64.89
20	1	1000	0.1	0.25	97.87

Table 2. Summary of RBF algorithm for Phase I

# Neurons	Spread constant	% correct	MSE
10	0.1	47.87	0.98
10	0.25	90.96	0.98
10	0.5	78.72	0.98
20	0.1	59.57	0.98
20	0.25	77.66	0.98
20	0.5	92.55	0.98

Table 3. Confusion matrix of RBF algorithm for 20 neurons and 0.5 spread constant

		Prediction		
		+1	-1	Total
Actual	+1	66	0	66
	-1	0	108	108
	Total	66	108	174

Phase II:

Table 4 shows the results of the back propagation with momentum algorithm in phase II. Similar to phase I, the network performs well with a small learning rate of 0.01 or 0.1, which allows the weights can be gradually adjusted throughout the entire dataset. When the learning rate is at 0.5 combined with a momentum parameter of 0.1, the network does not perform well. Best performance is obtained with 10 neurons, a learning rate of 0.1, and momentum parameter of 0.25.

Table 5 shows the results of the radial basis function network. Again similar to phase I, the overall performance is slightly better when the number of neurons is increased from 10 to 20. With 10 neurons, performance is best with a spread constant of 0.25. With 20 neurons, performance is best with a spread constant of 0.5. Table 6 shows the confusion matrix of the best case.

Table 4. Summary of back propagation algorithm for Phase II

# Neurons	Training time (seconds)	Epochs	Learning rate	momentum parameter	% correct
10	1	1000	0.01	0.5	96.65
10	1	178	0.5	0.1	78.18
10	1	1000	0.1	0.25	100
20	1	1000	0.01	0.5	95.45
20	1	146	0.5	0.1	40
20	2	1000	0.1	0.25	98

Table 5. Summary of RBF algorithm for Phase II

# Neurons	Spread constant	% correct	MSE
10	0.1	33.64	0.89
10	0.25	55.45	0.89
10	0.5	95.45	0.89
20	0.1	63.64	0.89
20	0.25	73.64	0.89
20	0.5	80.91	0.89

Table 6. Confusion matrix of RBF algorithm for 10 neurons and 0.5 spread constant

		Prediction		
		+1	-1	Total
Actual	+1	64	0	64
	-1	0	41	41
	Total	64	41	105

In Table 7, as expected, the support vector machine is the most powerful NN algorithm. It can lead to a 100% classification regardless of the value of the cost of misclassification (C or Box Constraint in Matlab). Despite the overall acceptable performance of backpropagation and radial basis function, it is more effective to work with support vector machine because there is always a chance of increase in complexity of geometry of specimen under consideration.

Table 7. Summary of SVM algorithm for Phase II

C (Box constraint, cost of misclassification)	% correct
100	100
500	100
2500	100

4. Conclusion

This paper successfully demonstrates that NN can do the repetitive work for the decision making in quality control in a real manufacturing environment. Three architectures were tested. It can be seen that for a relatively simple classification, a radial basis function model works effectively, while for a more complexity situation, a support vector machine model can achieve desired results.

For future work, feature function matrix can be examined. If function data can be listed at the level of every feature of the part, then the machine can be trained to take the decision to scrap, rework or "use as is" based on the function of the feature and the defect on it. Meanwhile, if the machine can be trained to visually view the defect[11], which will also lead to automating minor repetitive decisions (e.g.: scratches, tool marks, galling of threads etc.).

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